

**PARTIAL LEAST SQUARES PATH MODELLING OF UMP STUDENTS'
ATTITUDES ON STATISTICS ACHIEVEMENTS**

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ABSTRACT

The objective of this study is to examine the structural relationships in the hypothesised model that consisted of antecedent constructs of students' attitudes i.e. Affect, Cognitive Competence, Value, Difficulty, Interest, and Effort and their impacts on the statistics achievement. This study employed an experimental survey design which involved 718 undergraduate engineering students who enrolled in applied statistics courses in Universiti Malaysia Pahang. The samples were from different faculties such as Faculty of Industrial Sciences and Technology, Faculty of Electrical and Electronic Engineering, Faculty of Civil Engineering and Earth Resources, Faculty of Chemical Engineering and Natural Resources, Faculty of Industrial Management, Faculty of Computer Systems and Software Engineering, Faculty of Manufacturing Engineering, and Faculty of Mechanical Engineering. The Survey of Attitudes towards Statistics, with a seven point Likert scale was adopted and adapted from reliable instrument. The structural equation model through partial least squares estimation (SEM-PLS) using SmartPLS software was employed to evaluate the hypothesised relationships in the "Students Attitudes – Achievement towards Statistics Model". From the modelling results, it revealed that all the hypothesised relationships are significant at $p < 0.05$ (t -value > 1.645), one-tailed test by using 5000 bootstrapped samples. In other words, the antecedent constructs of students' attitudes towards statistics influenced the Statistics Achievement both directly and indirectly. Overall, the hypothesised structural equation model predicted 43.3% of the total variance in Statistics Achievement with a statistical power analysis of G*Power at 95% confidence level. In addition, the f^2 effect size for exogenous latent constructs and Q^2 predictive relevance for endogenous latent constructs are also positive, while q^2 effect sizes through *blindfolding* procedures are also acceptable. In conclusion, the empirical value showed that the model has the predictive capability in explaining the variances in the Statistics Achievement that are predicted by the antecedent constructs of attitude among the samples under study.

ABSTRAK

Objektif kajian ini adalah untuk menilai hubungan struktur dalam model hipotesis yang mengandungi konstruk antiseden sikap pelajar iaitu Afek, Kebolehan Kognitif, Nilai, Kesukaran, Minat dan Usaha yang memberi kesan kepada pencapaian statistik mereka. Kajian ini mengguna pakai kaedah tinjauan bereksperimen melibatkan 718 pelajar ijazah sarjana muda yang mengambil kursus statistik gunaan di Universiti Malaysia Pahang. Sampel diambil dari fakulti-fakulti berlainan iaitu Fakulti Sains dan Teknologi Industri, Fakulti Kejuruteraan Elektrik dan Elektronik, Fakulti Kejuruteraan dan Sumber Alam, Fakulti Kejuruteraan Kimia dan Sumber Asli, Fakulti Pengurusan Industri, Fakulti Sistem Komputer dan Kejuruteraan Perisian, Fakulti Kejuruteraan Pembuatan dan Fakulti Kejuruteraan Mekanikal. Soal selidik sikap pelajar terhadap statistic, dengan skala Liker 7 markat diguna dan diadaptasi daripada instrument yang berkebolehppercayaan. Pemodelan Persamaan Struktur dengan Perisian SmartPLS telah digunakan untuk menilai hubungan berhipotesis dalam “Model Sikap Pelajar terhadap Pencapaian Statistik”. Hasil daripada keputusan pemodelan, hubungan berhipotesis menunjukkan hubungan yang bererti pada $p < 0.05$ (nilai- $t > 1.645$) pada ujian satu hujung dengan menggunakan 5000 sampel butstrap. Dengan kata lain, konstruk anteseden sikap pelajar terhadap statistik mempengaruhi pencapaian statistik mereka secara langsung dan tidak langsung. Keseluruhannya, model persamaan struktur berhipotesis meramalkan 43.3% daripada keseluruhan varians dalam pencapaian statistik dengan analisis kuasa statistik G*Power yang baik pada aras keyakinan 95%. Tambahan itu, saiz kesan f^2 terhadap konstruk pendam eksogenus dan Q^2 keterkaitan ramalan untuk pembolehubah pendam endogenus adalah positif manakala saiz kesan q^2 melalui prosedur *blindfolding* adalah diterima. Kesimpulannya, nilai empirik menunjukkan model mempunyai kebolehan ramalan dalam menerangkan varians di dalam pencapaian statistik yang diramalkan oleh konstruk anteseden sikap dalam kalangan sampel yang dikaji.

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LIST OF SYMBOLS

α	Internal consistency
%	Percentages
f	Frequency
f^2	Effect size for exogenous variable
R^2	Coefficient of determination
R^2_{adj}	Coefficient of determination (adjusted)
$R^2_{included}$	The R^2 value of the endogenous latent constructs when a selected latent construct is included.
$R^2_{excluded}$	The R^2 value of the endogenous latent constructs when a selected latent construct is excluded.
Q^2	Blindfolding and predictive relevance for constructs
q^2	Effect size of Q^2
$Q^2_{included}$	Predictive relevance for endogenous all endogenous constructs that include all constructs
$Q^2_{excluded}$	Predictive relevance for endogenous constructs after one construct deleted
ξ_{ij}	Latent constructs
x_{ij}	Indicators
N	The number of indicators assigned to the constructs
σ_t^2	Variance of indicator t
λ	Loading values
\sum	Summation
$H_1 - H_{10}$	Hypotheses

LIST OF ABBREVIATION

UMP	Universiti Malaysia Pahang
SATS	Survey Attitude towards Statistics (version 28 and 38)
SAS	Statistics Attitudes Survey
ATS	Attitude Survey Statistics
STARS	Statistical Anxiety Rating Scale
UKM	Universiti Kebangsaan Malaysia
H_i	Hypothesis ($i = 1, 2, \dots, 10$)
Af_i	Affect Indicators ($i = 1, 2, \dots, 6$)
CC_i	Cognitive Competence Indicators ($i = 1, 2, \dots, 7$)
V_i	Value Indicators ($i = 1, 2, \dots, 9$)
D_i	Difficulty Indicators ($i = 1, 2, \dots, 7$)
I_i	Interest Indicators ($i = 1, 2, \dots, 5$)
E_i	Effort Indicators ($i = 1, 2, \dots, 4$)
SEM	Structural Equation Modelling
PLS	Partial Least Squares
CR	Composite Reliability
AVE	Average Variance Extracted
SD	Standard Deviation
Cog-Com	Cognitive Competence
Sta-Achi	Statistics Achievement
Std.beta	Standard Beta or Beta Coefficients
SE	Standard Errors

SSO	Sum of Squares of Observations
SSE	Sum of Squared of Errors
CMV	Common Method Variance

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Students are expected to learn, understand, know and be able to validate certain skills, behaviours, and attitudes. Although, Learning methods have been illustrated and defined by a variety of different learning theories, and among the popular learning theories in the 20th century are the cognitive and behavioural theories (Emmoglu, 2011). Cognitive learning theory is focused on the learning strategies “used in arranging the process of acquiring knowledge” (Kesici et al., 2009, p.530); whereas behavioural learning theories refer to relatively enduring change in “hierarchical, observable, and measurable behaviours” (Emmoglu, 2011, p.1). According to Kesici et al. (2009) and Lavasani et al. (2011) learning strategy includes gender, locus of control, psychological needs, emotion, motivation, cognitive, metacognitive and behavioural activities. Further, Martin (2010) and Suanpang et al. (2003) reported that learning strategy is divided into cognitive strategy and metacognitive strategy. Cognitive strategies refer to any kind of behaviour, thought or action that students employ when trying to learn, while metacognitive strategies refer to the learners’ opinions and beliefs about learning and to the active regulation of their learning process (Vermunt, 1996).

The perception of learning includes different variables such as process, content, and scope that are correlated with both the learner and the process of learning (Kesici et al., 2009). As stated by Seddon (1978), Blooms' model for educational scientists categorized learning process into three domains, which are affective domain, cognitive domain and psychomotor domain. Affective domain refers to learners' attitude, beliefs, values and emotions and although it has not earned considerable attention, it has a significant role in education (Seddon, 1978). Also, cognitive domain refers to knowledge structures and abilities, and it has earned much attention and has been the primary goal of education in many fields (Seddon, 1978). Hence, psychomotor domain, on the other hand, deals with physical movement, coordination and motor skills. So, learners' expectation is related to affective learning which has a role in guiding learners' actions (Emmoglu, 2011).

In education, statistics is defined as "the study of the collection, organization, analysis, interpretation and presentation of data" (Dodge, 2006); or as the "science of learning from data" (Emmoglu, 2011, p.3); and statistics courses are regarded as important subjects for students to learn in higher education (Nasser, 2004). The concept of statistics widely used in various fields such as economics, business, science, social science and technology, statistics is reported through various mass media such as television, the internet and newspapers. Also, statistical skills involve a collection of abilities such as statistical language and procedures as well as statistical reasoning, and the applicability of statistics is significant with rapid increase in its usage (Ashaari et al., 2011; Brown and Kass, 2009 and Nasser, 2004). Further, the growth of massive computation for data analysis makes statistics vital as it is a unique combination of actual world of mathematics, epistemology and computational academic activities (Brown and Kass, 2009).

The economics has long been shaped at least in part by statistics (Copeland 1955); as it has allowed businessmen to directly access statistical material and carry out their daily policymaking tasks (Cameron, 2004). Hence, government information policy is largely concerned with the management of information resources (Nilsen, 1998); where statistics have assisted leaders and managers carry out their duties such as in administration, population census, implementing any policy, examine its pros and cons

among the society, reports of political election and estimate the figures of national incomes (Ramirez et al., 2012). So, these are some of the reasons for the need to understand statistics.

First, statistics courses are a compulsory subject in many fields, such as economic, education, engineering, social sciences and natural sciences, as statistical knowledge and technological devices have important roles in data analysis and statistical learning. Although, statistical software packages can improve statistical application and decrease the overemphasis of mathematics in statistics courses, making the focus of statistics education more on conceptual understanding and less on the mechanics of the mathematical procedures (Emmoglou, 2011 and Ramirez et al., 2012).

Second, performance of students in the statistics teaching-learning process and assessment was reported to be related to students' attitude and perceptions towards statistics (Dempster and McCorry, 2009). According to Gal et al. (1997) the most importance aims of statistics education are to prepare students to deal efficiently with the statistical aspects that are relevant and related to their daily lives, especially in decision-making process. Formal exposure to statistical analysis and research methods would allow students to understand the problems better (Ramirez et al., 2012). For example, during the production of commercial material, statistics knowledge is used to adjust the request according to the available sources. So, statistics learning is a concept that indicates process, content and scope related to both the learner and teaching process (Kesici et al., 2009 and Lavasani et al., 2011).

Third, a lecturer affected the learning process and plays an important role in his students' learning process while having a significant influence, either directly or indirectly, on their achievement in statistics (Lovett et al., 2008). As stated by Kvam (2000) the greatest effect on students' attitudes and achievement towards statistics are lecturers with teaching experience, statistical training and interest in statistics courses. However, the quality of a lecturer teaching statistics, the quality of the learning institutions and the quality of students studying the subject would influence the teaching quality in statistics, which in turn affects students' outcome (Papanastasiou, 2002). Numerous studies have showed that students' attitude towards statistics improved when

suitable instructional methods are adopted (Khavenson et al., 2012; Ashaari et al., 2011 and Schau, 2003a).

In the last, over the past few decades, the development of an improvement in statistical training has taken place. Students in higher education need to improve their attitudes towards statistics. Attitudes towards statistics have been defined as the measure of a students' positive and negative feeling, action or thinking towards the subject in terms of relevance that indicate the disposition or belief of a person with regard to statistics (Ashaari et al., 2011; Judi et al., 2011; Khavenson et al., 2012; Mahmud, 2008 and Schau, 2003a). Six constructs of a student's attitude towards statistics, which are cognitive competence, affect, value, difficulty, interest and effort, have been introduced by several authors (Schau, 2003a; Ashaari et al., 2011; Estrada et al., 2005; Judi et al., 2011; Khavenson et al., 2012 and Mahmud, 2008); where each attitude dimensions is divided into positive, neutral and negative attitudes (Ashaari et al., 2011). Although, included students' attitudes others constructs have significant related to statistics achievement, such as statistics anxiety, mathematics backgrounds, statistics skills, self-confidence and gender.

1.2 PROBLEM STATEMENTS

According to Kesici et al. (2011) statistical learning is vital for solving problems and empowering critical thinking, but solving problems and critical thinking need positive attitudes towards statistics, which implies that students should be able to construct their knowledge and increase his/her positive attitude towards statistics learning. It is noted Emmoglu et al. (2012) and Onwuegbuzie and Wilson (2003) that students' statistics achievements effected with high level of negative attitudes and statistics anxiety. Also, the other variables which are related to learners' lack of understanding in the fundamental concept of statistics and influenced the process of statistics learning as such students' stress regarding to examination, lack of confidence, fear form statistical formula, massive computation and semester system being used in the university (Permulaan and Wook, 2011; Emmoglu, 2011; Karupiah, n.d and Gal and Ginsburg, 1994).

Statistics anxiety is defined as “the feelings of anxiety encountered when taking a statistics course or doing statistics” (DeVaney, 2010, p.1). The statistics anxiety is a universal problem in the progress of learning and teaching of statistics courses (Macher et al., 2012 and Onwuegbuzie and Wilson, 2003). It was found Onwuegbuzie (2004) that approximately 66% to 80% of graduate students experiencing uncomfortable of level of statistics anxiety. Also, the high level of statistics anxiety leads that students’ views of statistics have become negative, and consequently, statistics courses are often delayed until the end of programs (Onwuegbuzie, 2004).

Another problem faced by the students are fear of mathematics and lack of prior knowledge in statistics (Karupiah, n.d.). Although, it is found that two dimensions of mathematics background related to attitudes toward statistics which are the more or less mathematics - oriented and mathematic grades obtained in secondary education (Carmona et al., 2005 and Sorge and Schau, 2002). However, the students’ fear from mathematics (numbers and formulas) and students’ lack of prior knowledge has influences in effective statistics learning (Carmona et al., 2005). According to Awang-Hashim et al. (2002) the other constructs i.e. mathematics self-concepts, students’ attitudes towards mathematics and home educational resources were the strongest factors that affected Malaysian students’ statistics learning.

Finally, the faculty of Industrial Sciences and Technology, Sciences program announced applied statistics course for undergraduate engineering students per semesters in Universiti Malaysia Pahang. Table 1.1 represent the students’ performance and statistics achievement from 2011 to 2014 that enrolled in applied statistics courses.

Table 1.1: Students performance in statistics course 2011-2014

Sessions	Semesters	Passed	Failed	Total
2011/2012	Second	562	235	797
2012/2013	First	706	164	870
2012/2013	Second	765	185	950
2013/2014	First	643	283	926
2013/2014	Second	693	141	834

Table 1.1 represent that 797 students who taken applied statistics courses in the second semester of 2011, about 562(70.51%) of them passed, while more than 235 (29.49%) of students failed from statistics courses. Meanwhile, in the academic year of 2012 students were more active and their achievement slightly increased 735 (80.82%) and about one-fifth of students' were failed from their statistics courses. Since, in 2013 also reported around 668(75%) of students' earned the adequate score and one-fourth of them failed the applied statistics courses. For more information you can see in Appendix H. In order to combat with above problems, attitude towards statistics is an important issue in statistics education. On top of that, it is important that further research on the role of attitudes towards statistics should be conducted to determine appropriate learning strategies in the statistics class in order to decrease the negative attitudes Mahmud (2009); increase positive attitude towards statistics (Gal et al., 1997); reduce statistics anxiety Onwuegbuzie (2004); to improve statistics achievement (Kesici et al., 2011).

1.3 RESEARCH OBJECTIVES

The objective of this study is to explore the structural relationship among students' attitudes towards statistics and statistics achievement by examining a structural model using partial least squares path modelling. The model is based on the "Statistics Attitudes-Outcomes Model" Emmoglu (2011) and "Statistics Attitude-Achievement Model" (Sorge and Schau, 2002) which is called "Students' Attitudes-Achievement towards Statistics Model".

This study examines the purposed hypothesised model and relationship between students' attitudes towards statistics (Affect, Cognitive Competence, Value, Difficulty, Interest and Effort) and statistics achievement (use of statistics in their professional life, students' confidence on the use of statistics, and expectation of students about grade earned from statistics courses). The objectives are:

1. To evaluate the instrument for measuring the dimensions of students' attitude towards statistics.
2. To empirically validate the hypothesized model of students' attitude on statistics achievements in Malaysian context.
3. To measure the degree relationships among the antecedent constructs of students' attitude towards statistics and statistics achievements.

1.4 RESEARCH QUESTIONS

The important questions addressed in this study are:

1. What is the nature of the inter-relationships between the six constructs of a student' attitudes towards statistics?
2. Is the variance in statistics achievements explained by the dimensions of students' attitudes towards statistics, which are affect cognitive competence, difficulty, value, interest and effort?
3. Are the relationships in the hypothesised model statistically significant and of practical importance?

1.5 IMPORTANCE OF THE STUDY

Overall, this study is important to learn statistical knowledge and the practice of statistics as highlighted by numerous studies regarding the significance of statistics learning process. Because, statistics have a negative reputation among statistics learning (Emmoglu, 2011). Although, statistics learners have anxiety and negative feeling towards statistics (Onwuegbuzie and Wilson, 2003). On the other hand, several studies suggested that statistics course are needed to be revised in a way to encourage students to learn statistics without anxiety and negative feeling (Dempster and McCorry, 2009; Emmoglu, 2011; Hilton et al., 2004 and Schau, 2003a). So, there is an increasing trend to make statistical courses compulsory in various fields of studies at the university level, particularly in the fields of engineering. However, students believed statistics courses as difficult subjects and consequently experience anxiety and negative attitudes. Hence, it is highly important to conduct more research on understanding the role of attitudes on statistics achievements.

Through this study, an increase in student problem solving skills and critical thinking could be accomplished by incorporating active learning strategies and this reduces the level of statistics anxiety. This would assist students develop their statistical reasoning and enhance what they have learnt by actually doing statistics, designing studies, collecting data, analysing their results, preparing written reports and giving oral presentations. Consequently, they would be able to read statistics, interpret statistical issues, calculate massive computation, data analysis and obtain desired learning outcomes.

Statistics has become one of the compulsory subjects in the generic fields of engineering, where engineers are continually exposed to data collection, data recording and manipulation, data analysis, generating predictive models and creating inference from the data. However, numerous studies have reported the negative attitudes among students studying statistics courses, which consequently affected their learning process. Thus, this study is significant to help engineering students learn statistics without anxiety and have positive attitudes towards the subject in order to effectively use the statistical skills in their professional life.

On top of that, the significance of this study includes the following. This study is based on Statistics Attitude-Achievement Models' application of impact of engineering students attitudes on achievement in statistics (Sorge and Schau, 2002) and Statistics Attitude-Outcomes Models' application of impact of social and natural sciences students attitudes and achievement in statistics (Emmoglu, 2011). The statistical model suggested in this study would contribute to the review of literature by investigating the relationship between some cognitive and affective components in the concept of statistics education. Furthermore, the findings obtained from the study would help investigators adapt the recommended model to different subjects, such as social sciences, natural sciences, engineering, and mathematics education.

In addition, the study utilizes a reliable, validated and hypothetically established instrument, which is the Survey of Attitude towards Statistics (SATS) (Schau 2003b); to measure students' attitudes towards statistics and statistics achievement, and thus the findings are expected to contribute to the review of related literature.

Even though statistics courses for most of industrial science and engineering students' are compulsory in Malaysian universities (Permulaan and Wook, 2011 and (Awang-Hashim et al., 2002). Also, there have been limited studies on statistics education in the country. Hence, the findings from this study would represent a sample of statistics education among engineering students as practised in Malaysia as the study is conducted in Universiti Malaysia Pahang.

Finally, the current study emphasises the importance of statistical tools in the fields of engineering, natural science and social science. However, the results obtained from this study would suggest new directions for future investigators. Based on the reasons presented, the current research would contribute in general to the progress of quantitative research analysis procedures by putting emphasis on students' attitude towards statistics and statistics achievement.

1.6 OPERATIONAL DEFINITIONS

The word of "*Attitude*" has been defined as "the spatial orientation or noticeable position of physical objects, such as statues or paintings" Emmoglu, 2011 and Schau, 2003a).

Attitudes towards Statistics are defined as individuals' learned positive or negative responses with respect to statistics (Emmoglu, 2011 and Mahmud, 2008). Attitude towards statistics is also refer to a multi-dimensional construct composed of three accepted pedagogical dimensions that can be analysed like Affective (believes, knowledge and self-perception), Cognitive (emotional and motivational) and Behavioural (performance and action tendencies) dimensions (Dempster and McCorry, 2009; Estrada et al., 2005; Nasser, 2004 and Schau, 2003a).

Affect is defined as students' positive and negative feelings concerning statistics (Morris, 2013 and Schau, 2003a).

Cognitive Competence is defined as students' attitudes about their intellectual knowledge and statistical skills when applied statistics (Morris, 2013; Emmoglu, 2011 and Schau, 2003a).

Value is defined students' attitudes about the usefulness, relevance, and worth of statistics in personal and professional life (Morris, 2013 and Schau and Emmoglu, 2011).

Difficulty is refer to students perceived that statistics contents is difficult (Morris, 2013; Schau, 2003a and Sorge, and Schau, 2002).

Interest is describing the level of students' individual interest in statistics (Morris, 2013 and Emmoglu, 2011).

Effort is defined as the amount of work that students spend to learn statistics (Morris, 2013; Emmoglu, 2011 and Schau, 2003a).

Statistics Achievement was measured, in this study, using the teacher created courses assessment including quizzes, tests, assignments, and final exam (Sorge and Schau, 2002). In the current study, statistics achievement involve three constructs which are application of statistics in their professional life, students' confidence on the use of statistics, and expectation of students' about the grade earned from statistics course.

Structural Equation Model (SEM) is a "statistical methodology that takes a confirmatory (i.e., hypothesis-testing) approach to the analysis of a structural theory bearing on some phenomenon" (Byrne, 2009, p.3).

Partial Least Squares-Structural Equation Model (PLS-SEM) is a powerful and popular statistical approach that enables a researcher to explore relationships among a set of variables and identify the key pathways that exist among the variables (Hair et al., 2013). PLS-SEM consists of two constructs which are outer model and inner model.

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Students are expected to learn, understand, know and be able to validate certain skills, behaviours, and attitudes. Although, Learning methods have been illustrated and defined by a variety of different learning theories, and among the popular learning theories in the 20th century are the cognitive and behavioural theories (Emmoglu, 2011). Cognitive learning theory is focused on the learning strategies “used in arranging the process of acquiring knowledge” (Kesici et al., 2009, p.530); whereas behavioural learning theories refer to relatively enduring change in “hierarchical, observable, and measurable behaviours” (Emmoglu, 2011, p.1). According to Kesici et al. (2009) and Lavasani et al. (2011) learning strategy includes gender, locus of control, psychological needs, emotion, motivation, cognitive, metacognitive and behavioural activities. Further, Martin (2010) and Suanpang et al. (2003) reported that learning strategy is divided into cognitive strategy and metacognitive strategy. Cognitive strategies refer to any kind of behaviour, thought or action that students employ when trying to learn, while metacognitive strategies refer to the learners’ opinions and beliefs about learning and to the active regulation of their learning process (Vermunt, 1996).

The perception of learning includes different variables such as process, content, and scope that are correlated with both the learner and the process of learning (Kesici et al., 2009). As stated by Seddon (1978), Blooms' model for educational scientists categorized learning process into three domains, which are affective domain, cognitive domain and psychomotor domain. Affective domain refers to learners' attitude, beliefs, values and emotions and although it has not earned considerable attention, it has a significant role in education (Seddon, 1978). Also, cognitive domain refers to knowledge structures and abilities, and it has earned much attention and has been the primary goal of education in many fields (Seddon, 1978). Hence, psychomotor domain, on the other hand, deals with physical movement, coordination and motor skills. So, learners' expectation is related to affective learning which has a role in guiding learners' actions (Emmoglu, 2011).

In education, statistics is defined as "the study of the collection, organization, analysis, interpretation and presentation of data" (Dodge, 2006); or as the "science of learning from data" (Emmoglu, 2011, p.3); and statistics courses are regarded as important subjects for students to learn in higher education (Nasser, 2004). The concept of statistics widely used in various fields such as economics, business, science, social science and technology, statistics is reported through various mass media such as television, the internet and newspapers. Also, statistical skills involve a collection of abilities such as statistical language and procedures as well as statistical reasoning, and the applicability of statistics is significant with rapid increase in its usage (Ashaari et al., 2011; Brown and Kass, 2009 and Nasser, 2004). Further, the growth of massive computation for data analysis makes statistics vital as it is a unique combination of actual world of mathematics, epistemology and computational academic activities (Brown and Kass, 2009).

The economics has long been shaped at least in part by statistics (Copeland 1955); as it has allowed businessmen to directly access statistical material and carry out their daily policymaking tasks (Cameron, 2004). Hence, government information policy is largely concerned with the management of information resources (Nilsen, 1998); where statistics have assisted leaders and managers carry out their duties such as in administration, population census, implementing any policy, examine its pros and cons

among the society, reports of political election and estimate the figures of national incomes(Ramirez et al., 2012). So, these are some of the reasons for the need to understand statistics.

First, statistics courses are a compulsory subject in many fields, such as economic, education, engineering, social sciences and natural sciences, as statistical knowledge and technological devices have important roles in data analysis and statistical learning. Although, statistical software packages can improve statistical application and decrease the overemphasis of mathematics in statistics courses, making the focus of statistics education more on conceptual understanding and less on the mechanics of the mathematical procedures (Emmoglul, 2011 and Ramirez et al., 2012).

Second, performance of students in the statistics teaching-learning process and assessment was reported to be related to students' attitude and perceptions towards statistics (Dempster and McCorry, 2009). According to Gal et al. (1997) the most importance aims of statistics education are to prepare students to deal efficiently with the statistical aspects that are relevant and related to their daily lives, especially in decision-making process. Formal exposure to statistical analysis and research methods would allow students to understand the problems better (Ramirez et al., 2012). For example, during the production of commercial material, statistics knowledge is used to adjust the request according to the available sources. So, statistics learning is a concept that indicates process, content and scope related to both the learner and teaching process (Kesici et al., 2009 and Lavasani et al., 2011).

Third, a lecturer affected the learning process and plays an important role in his students' learning process while having a significant influence, either directly or indirectly, on their achievement in statistics (Lovett et al., 2008). As stated by Kvam (2000) the greatest effect on students' attitudes and achievement towards statistics are lecturers with teaching experience, statistical training and interest in statistics courses. However, the quality of a lecturer teaching statistics, the quality of the learning institutions and the quality of students studying the subject would influence the teaching quality in statistics, which in turn affects students' outcome (Papanastasiou, 2002). Numerous studies have showed that students' attitude towards statistics improved when

CHAPTER 3

PARTIAL LEAST SQUARES PATH MODELLING

3.1 INTRODUCTION

For confirming of the research models, researchers have been using the statistical analysis tools for several years. The statistical analysis tools separated in to two generation (Hair et al., 2013). The first generation statistical analysis tools dominated the research landscape through the 1980s, while since the early 1990s, the second generation statistical analysis have expanded rapidly and represent almost fifty percent of empirical research used the second generation of statistical tools (Hair et al., 2013). In this case we will use the partial least squares structural equation modelling (PLS-SEM) which is a kind of second generation of statistical analysis tools.

3.2 STRUCTURAL EQUATION MODELLING (SEM)

Structural Equation Modelling (SEM) is a “statistical methodology that takes a confirmatory (i.e., hypothesis-testing) approach to the analysis of a structural theory bearing on some phenomenon” (Byrne, 2009, p.3). SEM with latent constructs has become a quasi-standards statistical tools in psychology (Hu and Bentler, 1998); education, social sciences (Emmoglu, 2011) and marketing research for investigating the credibility of empirical hypothetical models that explain the interrelationship between a set of latent constructs (Henseler et al., 2012b) .

The objective of SEM analysis is to define the level of hypothetical model that is supported by targeted population (Lomax and Schumacker, 2012). Although, using SEM tools has several advantages (Larwin, 2007). First of all, SEM can measure the relationship between observed and unobserved variable without measurement error (Kline, 2005). Secondly, the reliability of measurement can be estimated in the absence of measurement error because the error can be isolated (Byrne, 2009). Thirdly, when the relationship among observed and unobserved variable are measured and are found to be complex, SEM is the top statistical methods for concurrently testing the multiple level in a complex mode (Larwin, 2007). Fourthly, SEM treats both endogenous and exogenous variables as random variables with errors of measurement (Golob, 2003). Finally, SEM can evaluate the models under test, as in many applications SEM is able to conduct investigative and confirmatory factor analyses (Emmoglu, 2011 and Hu and Bentler, 1998).

To better understand SEM, one needs to understand the models and results produced by SEM, as SEM refers to a family of related procedures that does not designate a single statistical technique (Kline, 2005). A brief explanation of the structure of SEM is as follows.

In SEM, those variables that are not directly measured are called constructs (unobserved variables or latent variables), which have two or more items (Byrne, 2009). In this study the latent variables are: Affect, Cognitive Competence, Difficulty, Value, Effort, Interest and Statistics Achievement. In SEM, a construct in path modelling is represented by a circle or an oval (Hair et al., 2013). So, path models in a diagram are used to visually exhibit the relationship among the construct and hypothesis that are examined when SEM is applied (Chin et al., 2003; Hair et al., 2013 and Tenenhaus et al., 2005). In this study, ten hypotheses, are put forward. In path modelling, those variables are able to measure directly called indicators, items, manifest variables or observed variable; which are a function of the latent variables that underlying constructs are supposed to represent (Hair et al., 2013). In this case, the observed variables are all those indicators (all questions) that are measured students' attitudes towards statistics and statistics achievement in the questionnaire survey form.

The Structural Equation Model included dependent variable and independent variables. It is noted, the independent variables (exogenous variable) are able to explain the other dependent variables (endogenous variable) (Hair et al., 2013). In other words, exogenous latent variables are synonymous with independent variables, and that their causes are unknown and fluctuation in the values of other variables to be represented in the model (Byrne, 2009). Overall, in this study, there is only one exogenous variable, which is Difficulty. All other constructs that are being explained in the model are endogenous constructs, where endogenous variables are synonymous with dependent variables (Byrne, 2009); and the variables are explicitly caused by exogenous variables in the model (Kline, 2005). In this case, the endogenous variables, which are Affect, Cognitive Competence, Value, Effort, Interest and Statistics Achievement, are included in the model specification.

3.3 PLS-SEM PATH MODELLING

The path models are diagram which are used to show the hypotheses and constructs relationships that are investigated when structural equation model is applied (Hair et al., 2013, Hair et al, 2012 and Hair et al., 2011). Although, partial least squares (PLS) is a family of statistical tools that able to extend principal construct and canonical correlation analysis (Henseler and Sarstedt, 2013 and Hair et al., 2013). The path model included constructs (i.e. factors, components, variables that are not directly measured) and indicators (i.e. items, manifest variables that are directly measured).

Researchers who want to examine their complex models by testing structural equation model (SEM) with interaction effects of latent variables could use partial least squares (PLS) path modelling (Henseler and Chin, 2010); the SEM is able to investigate tests the hypotheses about relationships between all the constructs in the hypothesised model (Hoyle, 1995).

Partial least squares–structural equation model (PLS-SEM) is a powerful and popular statistical estimation that enables a researcher to explore relationships among a set of variables and identify the key pathways that exist among the variables (Hair et al., 2013). The resultant web of relationships can serve as a very useful guide for